

**Language Family Analysis and Geocomputation:
Machine Learning Methodologies and Geospatial Considerations for Language
Phylogenetic Analysis in R**

by

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Bachelor of Science in Mathematics, University of Pittsburgh, 2020

Submitted to the Graduate Faculty of the
University Honors College in partial fulfillment
of the requirements for the degree of
Bachelor of Philosophy

University of Pittsburgh

2020

UNIVERSITY OF PITTSBURGH

UNIVERSITY HONORS COLLEGE

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With the fast-growing pace of advancements in computer science, mathematics, and linguistics, great strides have been made in each field. Here, work regarding the analysis of language families will be presented in an argument for the acceptance of results that are derived from a computational means. Specially, this research leverages machine learning methodologies to gain insight into the relationship between, and classification of, different languages and language families. Further, the higher rate of the availability of data regarding the geospatial aspects of a language spreading allows for the incorporation of this data into an analysis of language spread. This research lays the foundation and establishes a framework in which these two aspects, computational analysis and geospatial data, are intertwined to offer a perspective and glean insight into language.

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Preface

This research is the culmination of extensive interviews about the facets of language and computation and would not be possible without the aid of many individuals. Thank you to Professor Alan Juffs, Professor Melinda Fricke, and Professor Na-Rae Han for linguistic expertise and fostering a sense of curiosity. Thank you to the several mathematics instructors that have aided this research both directly and indirectly. Thank you to the University of Pittsburgh for establishing the BPhil program and supporting the students through it, particularly Mr. Jason Sepac, and Dean David Hornyak.

Special gratitude is shown to those individuals willing to sit and member the defense committee: Dr. Michael Schneier, Dr. Na-Rae Han, Dean Laura Dice.

The grandest thanks of all to Dr. Jeffrey Wheeler, who insisted he not be mentioned. Without you, barely anything in my college career, particularly in research, would have been accomplished.

This research focuses on languages and their spreading. In discussions “languages spreading” will be taken to mean “people(s) who speak the language migrating over time”. That is, the spread of language is synonymous with the spread of people.

1.0 Introduction

With many advancements in the world of computing, vastly different fields of study have found advancements achievable with the use of computational methods. Researchers' goals have been given a new perspective on what is possible by leveraging the methodologies of computing science. Further, some of these areas of study have seen the development of entirely novel sub-fields due to the increase in application of technology. One of the greatest examples is linguistics.

Linguistics is the study of language in all of its facets: from the pronunciation of words (phonetics), to how thoughts are constructed and articulated (morphology and syntax), to how it is acquired and processed in the brain (psycho-linguistics). As mentioned, a new sub-area has emerged applying the developments in computing: computational linguistics. We can see the new technologies of this in everyday life. Speech-to-text, auto-correct applications, and even language-learning software are results of this discipline that combines linguistics studies and practices with computing methodologies to create these new products.

One of the areas of linguistics that has seen less involvement with computational methods is phylogenetic analysis. This is the branch of linguistics that studies the way languages are grouped and classified together in terms of language family. The study is predicated on the axiom that languages change and evolve over time and have been doing so since their inception. The goal of phylogenetic analysis is to figure out which languages are related to which in the phylogeny, and further, to trace the history of languages and offer a complete anthology regarding their origin. The classical approach in this area of linguistics, referred to also as historical or comparative linguistics, has been a primarily qualitative examination of languages, referencing both temporal (the natural chronological change of words) and the spatial (using certain words for certain objects

in one's environment) aspect of language, as well as drawing upon the field of anthropology to supplement information. This line of effort has long been treated as a purely human endeavor, but this report will offer a computational approach to phylogenetic analysis.

The computational approach is key to this research: this study leverages developments in the area of machine learning to gain insights into phylogenetic analysis. Machine learning is an often-misunderstood term, synonymous with artificial intelligence. In the sense for this study, machine learning will be the umbrella term which covers a range of computing methods that a computer can employ to reveal insights into pattern recognition. It is these patterns that are being sought in the area of phylogenetic analysis. That is, machine learning will be used to determine patterns among language change.

The main machine learning methods that will be used in this study are clustering and gradient descent. Clustering is an algorithm that allows a user to input a group of items, each compared to each other by some metric of similarity and offers a hierarchical structure to them. This means that, given a list of items and a way to realize how similar or different each item on the list is to the other items, a computer can use a rigorous algorithm to generate groupings of the items. The closer one item is grouped to another reflects a closeness in similarity. With this in mind, it is a natural extension to see how this method would have applications in phylogenetic analysis.

The second machine learning method that is used in this study is gradient descent. This is a method that, when given a slope of a function, is able to find the direction that has the steepest decline. The surface that is used to give an image of the function is the gradient, and any decline from an original point is a descent, hence the term gradient descent. But when the focus is on a real-world model of languages and how they spread across the Earth, capturing the spatial travel

of the people who speak a language will of course be important. In order to resolve this, geospatial data is necessary. This study uses this data in order to inform the model of which direction languages are likely to spread.

Crucial to the understanding of languages and the ways that they can evolve over time is the concept of geospatial considerations. That is, where a people who speak a language are located has a supreme bearing on its development and change. The way a language spreads cannot be isolated from its geography. Given this, research here offers a way to incorporate at least some of these considerations into a computational model of how language spreads. This is another natural application of the gradient descent method discussed earlier.

This study will use elevation as a key informatic to influence a model of how languages change. The natural formation of the area over which the way people who speak a language move will of course dictate to some extent how isolated languages are and can decrease the likelihood to evolve and change together. For example, the languages of the Indian sub-continent and present-day China have long been separated by the Himalayan Mountains. Thus, comparative and historical linguists can confidently conclude that there has been little interaction between the two and the speakers of one were not able to travel to the speakers of another, due to this barrier. Indeed, we see this principle's effects when comparing different regions.

Geographic areas with mountainous terrain, such as the island of Papua New Guinea or the Caucas Mountains have a dramatically high number of languages spoken in them, while vast spaces of planes and rolling hills, such as Central and Norther Asia as well as parts of North Africa, at different times through history, saw the spread of one single language or small language family (Mongol and Arabic, respectively).

As discussed, there appears to be a natural connection between the classical methods of language family analysis, and the spread of languages and the machine learning methods available to researchers today. Thus, blending the two together is suggested to provide a fruitful line of effort that will achieve results that can be considered to add to the understanding of these topics. This research leverages machine learning algorithms to analyze the similarity of languages and computationally group them into phylogeny, as well and provide a model for gaining insight into how these languages would have spread.

As mentioned, there have been many advancements in computing leading to large leaps in, and the formation of, computational linguistics. However, the focus has remained largely in things regarding information technology, such as text-to-speech and autocorrect. And while these things have been profitable, many large-scale endeavors, such as analyzing language families have been left alone and inspected through classical methods. Linguists and anthropologists have worked together to trace human languages over time and space seeking to piece together a historical narrative of both people and language. These lines of effort have primarily focused on archeologic and anthropologic excavations as well as the comparative method in linguistics. This research offers not only new insights into these fields but expands upon new line of effort working in tandem with already established methods to learn more about the very same narrative.

2.0 Background

As with any multidisciplinary study, this research draws upon broad concepts and research from across multiple fields. This section will provide an organized background of previous methods which served as both inspiration and foundation for this research project.

2.1 Language Family Analysis

The origin of historical linguistics, the sub-field focused on the history of languages diverging from one another, traces its inception to the late 1700s (Campbell 2013), even though the questions of language origin and similarities have been investigated through antiquity. Notable names throughout history, such as Aristotle and the Brothers Grimm, have thought about language, and indeed any person learning a new language or even coming across one would draw upon the conventions of their mother tongue to expedite the learning process of a novel language. (A fact leveraged by some language teachers (Saphiu 2016).)

This project focuses on the comparative linguistic branch of historical linguistics, the discipline with the goal of comparing languages and ultimately placing them into families. This article aims to provide computational evidence for comparing the languages of the Indo-European language family. Indo-European is the term given to the languages which share a common ancestor, termed Proto-Indo-European (PIE), and have thus spread from Iceland to Eastern India. (Indeed, to the present day, the languages have spread farther than that, with the colonial era of English and Spanish speakers, as well as present day human migration.) A few languages to

represent the scope of Indo-European languages are given here: Albanian, languages of ancient Anatolia (Hittite), Armenian, Balto-Slavic Languages (Russian, Czech, Latvian,) Celtic languages (Gaelic, Irish) , Germanic languages (German, English, Icelandic), Greek, Indo-Iranian languages (Kurdish, Persian, Sanskrit, Urdu), Italic (Latin, Spanish, Italian)

While certainly not the first to make the claim, Sir William Jones, a judge from England, presiding in India at the time is most widely credited with bringing the idea of Proto-Indo European to the forefront of western language study (Patil 2003). Speaking English, Latin, and Greek, Jones began to notice similarities between the ancient sacred language of India and the European languages. Thus, a great leap forward in comparative linguistics was made.

Today, linguists have classified thousands of languages. But up until recently, these classifications have been made using what is termed, the comparative method. This is the classical method of determining the relationship of one language to another. While the precise and lengthy details of this process are outside the scope of this background, a summary would typically follow an outline such as:

1. Assemble words of same/similar meanings of the two languages
2. Establish the smallest possible correspondence
3. Determine if there is enough similarity to justify significant relationships.

Of course, a great deal of training and care must be taken to set out on tasks such as these.

The next step for comparative linguistics is to then take this process and determine a history of language change, which typically manifests itself as a language family tree. (It is important to note that there are of course competing theories of how languages change, but this research is primarily focused on the family tree model, which is most prevalent.) This family tree reflects the

ancestry of languages and gives a visually coherent way of understanding relationships: (Indo-European Languages n.d.)



Figure 1. An abbreviated family tree example of Indo-European Languages

The goal of comparative linguistics is thusly to correctly categorize all possible human languages. This provides research not only with supplemental knowledge about the languages themselves, but the people who spoke them, and the world in which they lived. Naturally the field is fraught with confusion at placement of some languages, but linguistics have been able to reconstruct a great deal of the human language narrative through the comparative method.

The aspect of language change has also been very important to sociolinguists who look at the changing of words in the context of dialectal variation. This is a linguistic process in which speakers of the same language will, over time, begin to say the same word differently, often the precursor to a new language. There are famous and wide-spread examples of this such as “the Southern Drawl” or “Americano” Spanish. Sociolinguists will often use data to construct a framework for discussing these dialects. William Labov is a famous sociolinguist who dealt with dialectal variation. His famous “r” study is a prime example of data-driven dialectal analysis for how languages change. He sought to identify how the pronunciation of the “r” was stratified through socio-economic status of New York’s population (Labov 1972). This research acts

similarly in trying to determine what factors may influence language change and how they be able to be modeled.

2.2 Computational Comparison

The primary aim of this research is to offer a viable and reliable alternative to the discussed comparative method. As computational efficiency grows, so does the scope of its application. Researchers have already applied computational methods to linguistics, and this research presents arguments for its continual use in historical and comparative aspects as well.

Thus far, many of these researchers have looked at comparative linguistics through the lens of computation. Much of their work has had a heavy statistic lean to it, and incorporates a variety of different strategies. Gerhard Jager of the University of Tübingen has written extensively on this topic. In 2019, he published a comprehensive approach to using computational methods in comparative analysis, going so far as to propose an entire workflow of the comparative method (Jager 2019). This article also offers multiple case studies to demonstrate that validity of these computational methods.

The key concepts that lay the foundation of these studies are phylogenetic relatedness and Bayesian statistics. Jager published work establishing the support of predicted language families with these statistical methods, that even the classical comparative method had struggled to conclude definitively (Jager, Support for linguistic macrofamilies from weighted sequence alignment 2015). This paper, among others, uses the ideas of posterior and prior probabilities, trademarks of Bayesian statistics. Chang et al. also used computational methods to support claims predicted by classical methods in linguistics. Their research provides evidence for the Proto-Indo-

European originating in the Kurgan Steppe (present day Ukraine), a long standing and popular conjecture. It makes use of both the Bayesian statistics mentioned earlier and a probability structure known as Markov chains to establish conclusions about the time of divergence based on their phylogenetic relatedness (Will Chang 2015). Another important article which served as inspiration for this research also drew upon Bayesian statistics when analyzing Semitic languages (Arabic, Hebrew, Amharic, etc). These languages were not only analyzed with phylogenetic analysis to establish genetic relationships, but considerations were given to inferred dispersal of the people who spoke the language (Andrew Kitchen 2009). This indicates the importance of geospatial data, and these projects indicate the fruitful application of computational methods in comparative linguistics.

These projects all had a very high level of statistical basis for them. This present research focuses on a new strategy for analyzing languages in a more discrete and non-parametric strategy. This research employs edit distance as a way to establish similarity between two languages. Edit distance is a measure of how much one word needs to be changed to become another. Words like “cat” and “hat” have a small edit distance, while words like “cat” and “hippopotamus” have a much larger one, as intuition would indicate. Formally, edit distance is often thought of as the minimum number of edits (usually from a predetermined set of possible operations) that can be done on a string of characters in order for one string to match another.

The most common forms of edits are insertion, deletion, swapping, and switching. These are all intuitive with examples following:

Table 1. Examples of edit operations

Operation	Pre-Edit	Post-Edit
Insertion	“sat”	“stat”

Deletion	“star”	“star”
Swapping	“sign”	“sing”
Switching	“crate”	“grate”

Table 2. Example of minimum edit distance

Editing “apple” to “happen”	
Begin	“apple”
Insertion, “h”	“happle”
Swapping, “le”	“happel”
Switching, “n”	“happen”
Edit Distance	3

Of course it is possible to edit “apple” to “happen” in a longer way with more steps. However, this compromises the closeness that the two strings would have. Thus, this research will only ever be focused on the minimum edit distance. This way, we will be able to draw on the work of the phylogenetic research previously mentioned, and use edit distance to establish the genetic relatedness between languages.

The scheme that will be used in phylogenetic analysis here is known as the Jaro Similarity, from the work of Matthew A. Jaro (Jaro 1989). This distance resulted in the most optimal results, and was thus selected for further use. It captures the similarity between two strings by taking into account and weighting the number of matching characters, as well as their order. The Jaro Similarity is found by comparing two strings (words), s_1 and s_2 by:

$$sim_j = \begin{cases} 0 & \text{if } m = 0 \\ \frac{1}{3} \left(\frac{m}{|s_1|} + \frac{m}{|s_2|} + \frac{m-t}{m} \right) & \text{otherwise} \end{cases}$$

where $|s_1|$ is the length of the first string, $|s_2|$ is the length of the second, m is the number of matching characters, and t is the number of transpositions. To help understand this, consider the following example:

$$s_1 = \text{"CRATE"}, s_2 = \text{"TRACE"}$$

C	R	A	T	E
T	R	A	C	E

$m = 3$ (R, A, E) are matching.

Now, to determine if T and C are close enough to be transpositions, check if they are closer than the following formula:

$$\left\lfloor \frac{\max(|s_1|, |s_2|)}{2} \right\rfloor - 1 = \left\lfloor \frac{\max(5, 5)}{2} \right\rfloor - 1 = \left\lfloor \frac{5}{2} \right\rfloor - 1 = \lfloor 2.5 \rfloor - 1 = 2 - 1 = 1$$

So, for this particular pair of words, T and C must be within one space of each other to be considered a transposition. Since they are of course not that close, $t = 0$, so:

$$sim_j = \frac{1}{3} \left(\frac{m}{|s_1|} + \frac{m}{|s_2|} + \frac{m-t}{m} \right) = \frac{1}{3} \left(\frac{3}{5} + \frac{3}{5} + \frac{3-0}{5} \right) = 0.6$$

Thus, “CRATE” and “TRACE” have a Jaro Similarity of 0.6. This with the range of 0 for no similarity, and 1 for an exact match.

To compare entire languages, of course, is much more involved. Instead of simply comparing one word from each language, this research uses the field standard list of words, known as the Swadesh list. This is a formalized list of approximately 200-word meanings (depending on version) that have been used by comparative linguistics to establish phylogeny. Published multiple times in the 1950s, Morris Swadesh created a list of word meanings that are theoretically less likely to change. This makes them prime candidates for establishing language families, as linguists are less likely to get thrown off by language change phenomena.

The lists contain different classes of words, though ones that are crucial to everyday speech and survival. Some deal with personhood, such as pronouns, and familial relationships. Others are words for things found in the environment, such as trees and game. Still, other classes refer to things such as numerals or abstract concepts. For this research Swadesh lists were gathered from Wiktionary, an open source research with a vast array of Swadesh lists available (Wiktionary 2020). Validating the lists is outside the scope of this research, however, accurate results were able to be obtained using them. An important note is that to ensure the integrity of linguistic processing, all the lists were converted to a Roman alphabet, with the nearest orthographic equivalent. An appendix with the entirety of the Swadesh List database is included for examination, as well as a resource to continue this research.

Another important computational tool that will be used is clustering. Clustering is a basic machine learning algorithm that takes a set of points, each with some notion of distance from one another, and determines from them the optimal way to cluster. These clusters are then considered to be groups with some form of relation to one another. These are then graphically represented in

a clustergram, also called a dendrogram, which reflects each level of clustering. One will note the similarity between the dendrogram and the family tree model of language phylogenetics, making an intuitive connection between the two.

2.3 Geospatial Data and Language Spreading

The other aim of this research is to add to the computational understanding the way languages spread spatially across the surface of the earth. This is dictated, naturally, by the way humans, the beings that carry a language move over time. Important to this research is the deviation from the anthropological and archeological lines of effort, and the establishment of a new conceptual framework for understanding human migration.

The feature that will be used in the model here is the idea of traversability. Even though there are multiple definitions and specific parameters to measure traversability, here it will be understood as a measure of the ease of a group of people to cross a space of land. Many factors must be taken into account, as this is a very abstract concept. The University of Massachusetts, with USDA Forest Service General Technical Report , and Oregon State University offer FRAGSTATS as a way to understand and measure traversability (Kevin McGarigal 1994).

University of Massachusetts gives:

“*Traversability index* is computed at the cell level and then averaged across cells in the focal patch. As a result, this metric requires substantial computations and may take considerable time to compute for a large landscape. In addition, this metric requires the user to specify an appropriate resistance matrix containing coefficients for each pairwise combination of patch types, as well as a scaling factor that governs the size of the maximum least cost hull; that is, the size of

the area surrounding the focal cell that is accessible given minimum resistance. The size of maximum least cost hull is based on a user-specified maximum distance or neighborhood distance. Based on this distance, FRAGSTATS computes the “bank account” needed to achieve a circular least cost hull with a radius equal to this distance.” (umass.edu/landeco n.d.)

While this research does not incorporate a resource bank, there are important features of note here. The first is that traversability is calculated for individual areas of land. That is, the terrain is considered to be a series of adjacent plots of arbitrary, but uniform, sizes such that each has its own measure of traversability. As the research today is concerned with Indo-European languages at large, data degrading minimum least cost hull and resource data is not available. To maintain a notion of traversability, this research use elevation to consider the way languages may move.

This does tend to reflect observations seen in the real world. As mentioned, flat plains ecosystems, such as the Mongolian Empire or North African coastal plains see a high level of uniformity throughout, while mountainous regions such as Papua New Guinea and the Caucus Regions have a great deal of language diversity. The reasons for this are often cited to be the terrain; the fact the mountains and valleys create pockets for languages to change independent of one another is the reason we see such stark contrasts. Thus, elevation will be the primary measure of the traversability for this research. For this research, elevation data was taken from the open source site GeoNames (GeoNames 2020)

2.4 Gradient Descent

The notion of traversability as a function of elevation gives way to a natural method in machine learning known as gradient descent. This is a technique that is found in the area of convex optimization. Developed by the famed mathematician Cauchy in 1847 (Lemaréchal 2012), it is employed to find the minimum value of a 2- or 3-dimensional function, by using the derivative, which in 3 dimensions is called a gradient, to determine minimum values. The algorithm works by assuming that the direction which has the steepest descent is the direction that needs to be taken in order to find the minimum values. The algorithm terminates when the rate of improvement becomes negligible; that is when moving around the surface no longer results in a significant enough decrease in the value of the function, gradient descent ends. This suggests that the process is not guaranteed to give an exact value, nor even a global minimum.

But, what is important here is not necessarily the minimum value that is achieved, but the path that gradient descent prescribes in its solution finding process. When taking the steps across the surface, and finding the gradient along it, the process records the path taken, the path of steepest descent. This is what will be useful in the research here. Considering the surface of the Earth to be like a function, we can consider that this path of steepest descent can be considered the path of least resistance for a group of people to take (ie. Not climbing over mountains), which in turn could be considered to be the route that has the highest degree of traversability. Thus, the use of gradient descent is a natural addition to this research, fitting in well with considerations for traversability. A figure example, and algorithm summary are included below for reference.

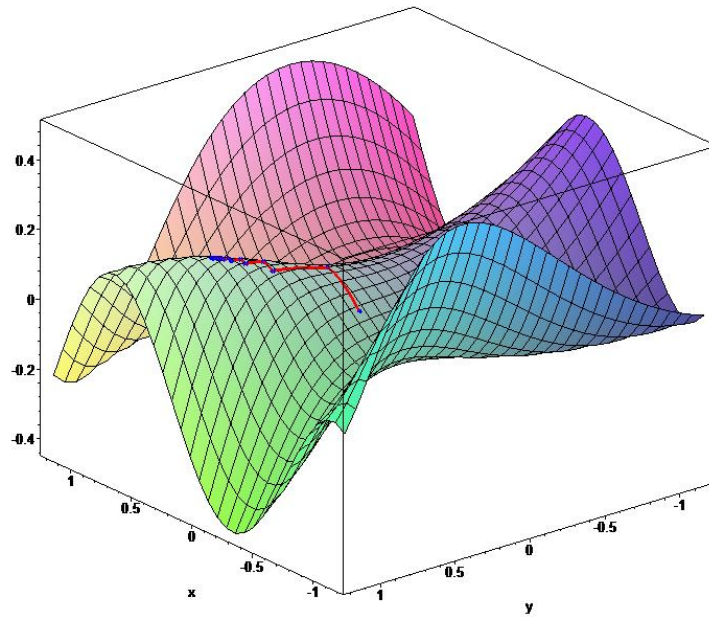


Figure 2. An example surface, with the path of steepest descent shown in red. (Gillis 2006)

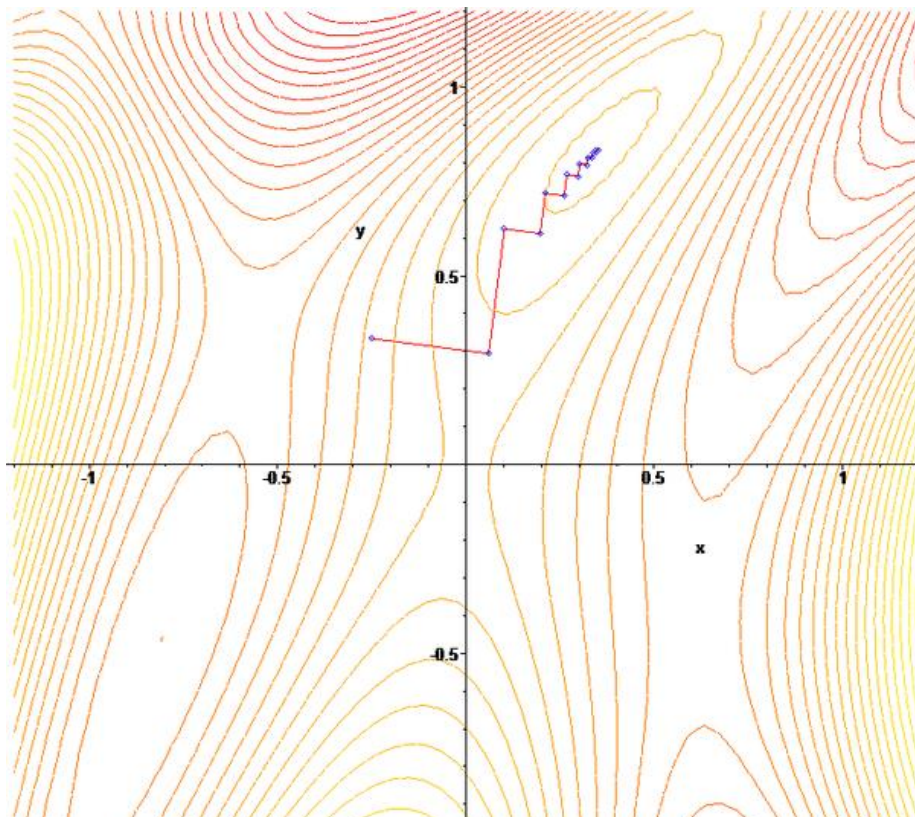


Figure 3. A contour map of Figure 2, again with the path of steepest descent shown in red (Gillis 2006)

Specifically, what this research will implement is an array of starting points. These will be representative of different starting points that groups of humans, the beings that carry language. Then, the gradient flow algorithm will be allowed to ensue, and these objects, the people, will be, predictably, find their local minima. This will of course exclude a lot of typical movement of people and emphasize things such as coastward movement, but the elevation will serve as a basis on which to expand.

Table 3. A tabular summary of the Gradient Descent Algorithm

GRADIENT DESCENT METHOD	
1) Calculate Gradient in all directions	
2) Take a step in the direction with least gradient (steepest descent)	
IF CHANGE IN VALUE LARGE	IF CHANGE IN VALUE SMALL
3) Return to step 1) and continue to iterate until change in value is small	4) End the algorithm, and take present value to be the minimum

The gradient descent algorithm will be used to determine what is called the gradient flow. This is a vector field that ascribes a direction to all points on a surface dictating their movement and how an object would be thought to flow through them. But putting the vector field on the Earth's surface, human migration can be modeled by the way a point flows through the field.

3.0 Technical Report

This section is focused on a summary and technical report of what was accomplished in this research. Contained here is a discussion of the methods used, as well as outputs from various portions of code. The software used is the open source software R Statistical Programming, along with various packages.

3.1 Dendrogram and Cluster Analysis

The first step in the program is the phylogenetic analysis. To create the desired graphics, the Swadesh lists were compiled and aggregated. To ensure the best possible results, the textual data had to be cleaned: all white space removed and characterized Romanized. Then, a distance matrix was created. A distance matrix is a data structure which allows hierarchical clustering to take place. This clustering is what gives rise to the family tree model as explained previously. The clusters can be considered to be the language family, and in order to see the clusters, similarity must be established. To do this, the Jaro Similarity was used.

The result of this is a similarity matrix. This is a data structure that contains the average similarity of one language to another, by finding the mean similarity of each that is paired on the Swadesh list. Conceptually, each word in the Swadesh lists for the language has its own similarity matrix, and all of these matrices are averaged to determine the overall similarity. This final matrix was then put through the clustering algorithm to create the clusters which would ultimately result in the following dendrogram:

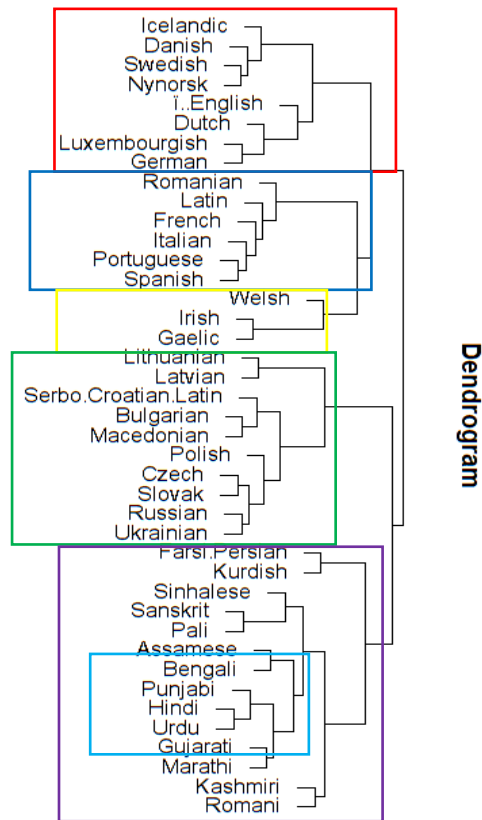


Figure 4. The outputted family tree model using the clustering algorithm.

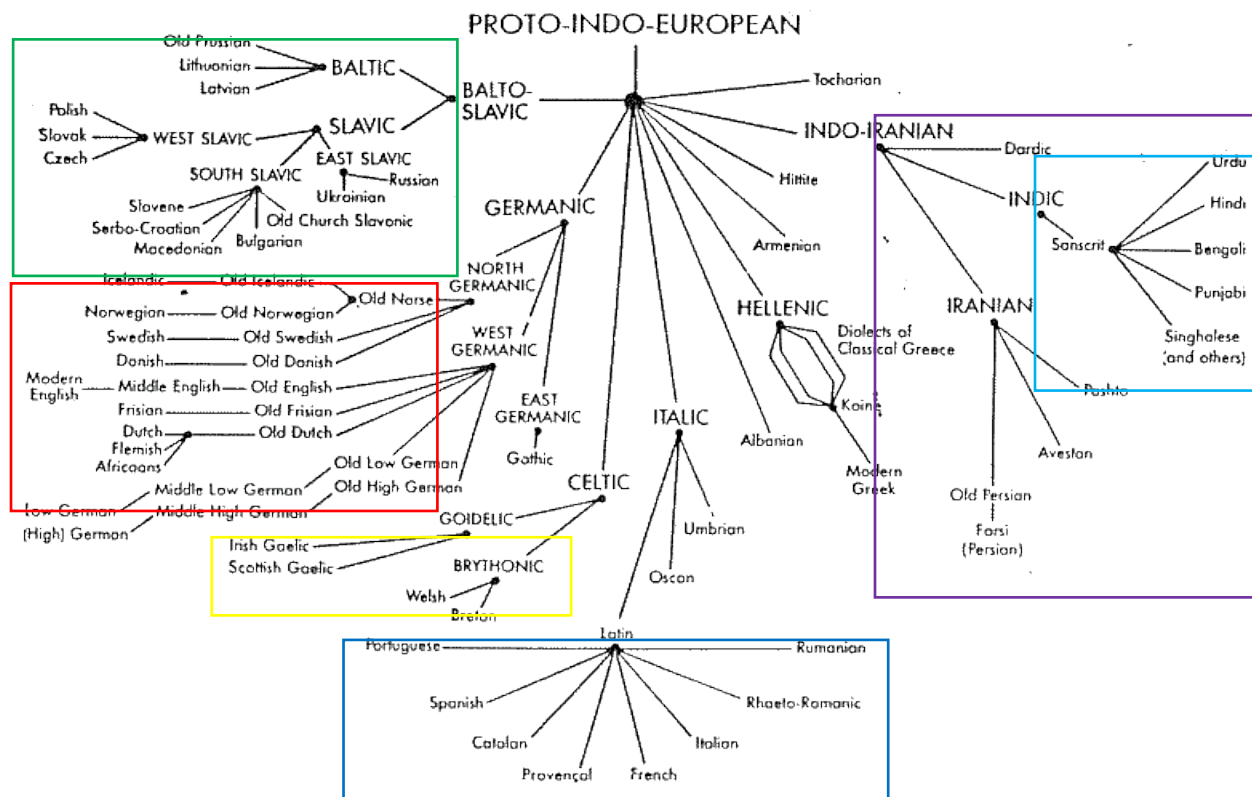


Figure 5. A already established family tree model for comparison (Gawron n.d.).

To create the outputted dendrogram, the vastness of the R library was utilized. First, the function “create.dist.matrix” was created as a customized function, which relied on the “stringdist” package for individual string calculations (Loo 2014). The matrix was made by simple index manipulation on a data frame. Then, the distances from one language to another were calculated with the default distance matrix computation function “dist”. The function “hclust”, from the same package (Team 2018) is the default hierarchical clustering method used, and “plot” to display the results.

As can be seen in the two diagrams, and the colored boxes highlighting the language families, the outputted dendrogram appears to do a good job of sorting the languages. There are specific measures that can be done to compare two different hierarchical clusters to measure how closely they match, but these would not be prudent here. The already established tree on the bottom is much more freely-formed than the one generated by the algorithm. It is not constrained by the same mechanics that govern the clustering algorithm.

When comparing the family tree model developed by the comparative method and the one created automatically, there are important features to note. The first is at the extreme levels of the cluster gram. There are some instances in which order is irrelevant. For example, it may be the case that Czech and Slovak are more similar to one another than Russian and Ukrainian, since they were clustered together before the second pair, suggesting a more recent split, but this is not guaranteed. However, there is still meaning in the fact that Czech and Slovak are in one group, while Russian and Ukrainian are in another: the two pairs of languages are indeed more closely related to those in their own grouping, than another, which is also reflected in the family tree resulting from classical comparative methods.

The second caveat is at the higher levels of clustering. Even though the Slavic languages are predicted to be more closely related to the Indo-Iranian languages than to the Germanic languages, one should be hesitant to affirm such strong claims. But, the notion that Indic languages are a subset of Indo-Iranian languages is of course true. A qualitative examination of these outputs does suggest validity for both the clustering method to modeling how languages spread, and the use of the Jaro Distance to determining word similarity.

It is not abundantly clear as to why the Jaro distance appeared to output the highest similarity between the computational and comparative methods. This may be considered a “black-box” programming method. However, reasons for this may include the fact that the Jaro similarity has much more a sliding scale approach. While elementary methods simply count steps, the Jaro distance considers things such as position distance between letters, and how much the characters of one string match another. With much more robust detection, the Jaro similarity is suggested to be useful for this line of effort.

3.2 Geospatial Modeling and Language Spread

As discussed, the second main focus of this research is to find a way to computationally understand how people could move through the environment. The program here will be utilizing gradient descent to capture the movement of people. To do this, gradient descent algorithms will be conducted across multiple areas to construct a gradient flow, which will serve as a reference for how an group of people may flow through the environment. First, a geospatial map was constructed

in R, and then from GeoNames.org, elevation data was imported for each of a series of coordinates, relating the positions on a map. A example is given below:

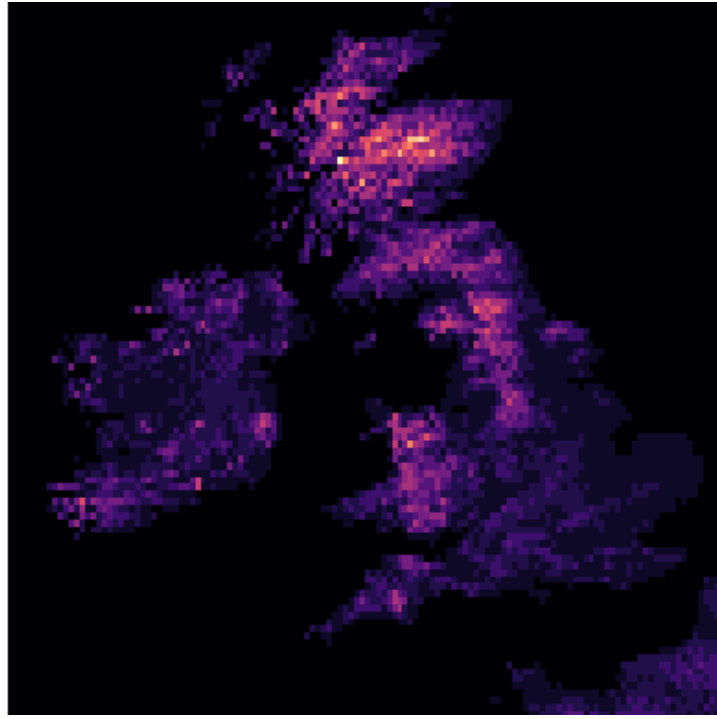


Figure 6. Elevation map of the British Isles, light colors reflect higher elevation.

This is an elevation map of the British Isles, along with northwestern France. Clearly visible are the Scottish Highlands, the English Lowlands, along with the mountainous regions in Wales. To construct high resolution elevation plots, especially for wider areas, requires higher levels of computing than is capable for research of this scope.

However, proceeding with the steps reveals interesting results. By using gradient descent and creating a gradient flow, or a vector field, we find a model of the world's surface for predicting the movement of people:

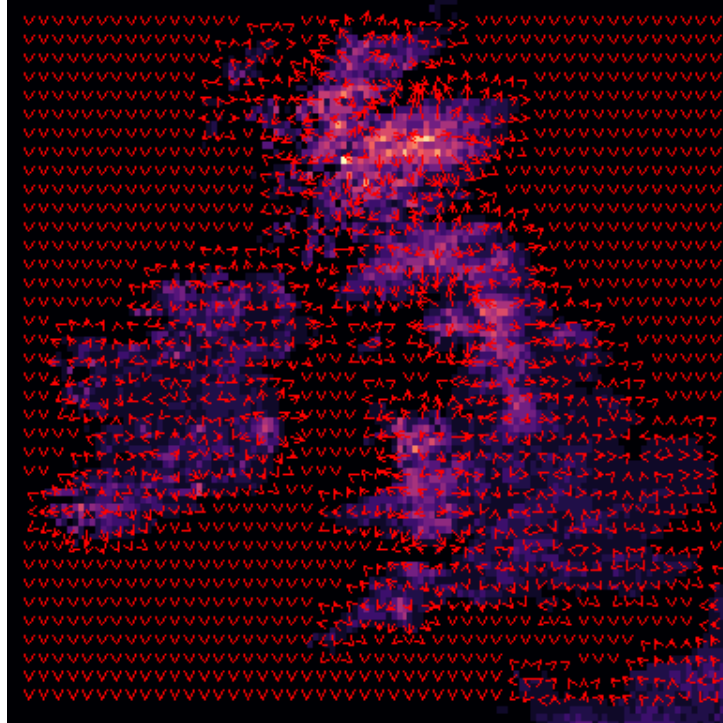


Figure 7. A gradient flow imposed on the surface.

The red arrows that are now super-imposed over the elevation map indicate the direction of the gradient flow, and indeed the modeled direction that a group of people would travel. The function that is being optimized is a raster function generated from the elevation data with the function “raster” (Hijmans 2019). This is now how the movement of groups of people can be modeled. The starting position of a point is inputted into the map, and the vector field dictates the movement:

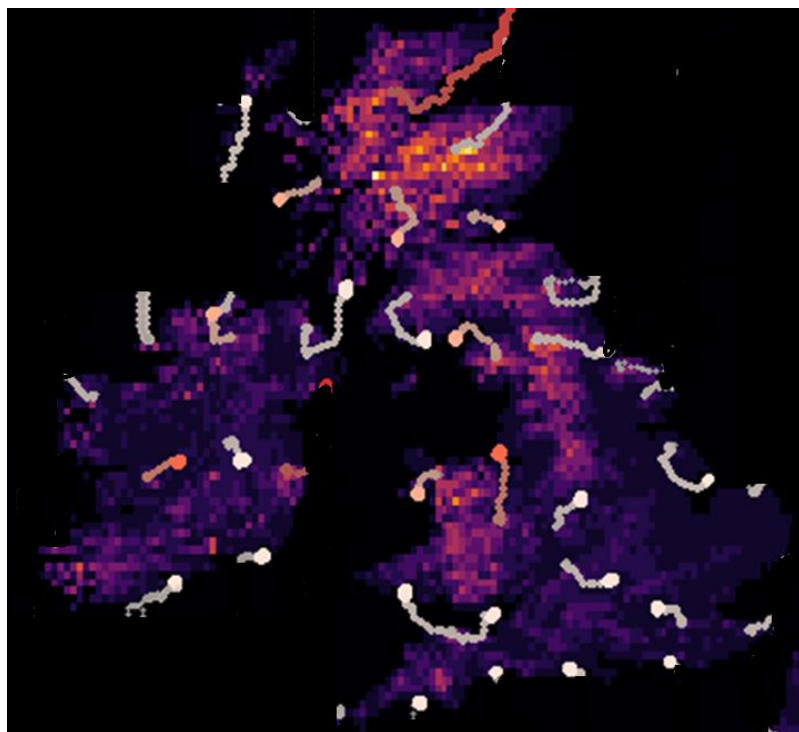


Figure 8. The movement of different initial conditions.

The small lines and curves now represent the movements of people given the gradient flow derived from the elevation map. In this example, we see resemblance of the people of present-day Scotland begin relatively isolated in the highlands, reflective of the development of Scot Gaelic, and some movement in the south of modern Ireland. These are both reflective of an accurate history. It is these paths that are the gradient descent algorithm at work: not so much as seeking to find the minimum, but displaying the path of least resistance, which would be considered to be the path that a group of people would take, with some probability. Thus, the results of this computational line of effort is a model for how language changes and how language spreads

4.0 Conclusion

Thys, what this research is able to present is two-fold. The first is an argument for the validity and usefulness of the Jaro distance for similarity, and the clustering algorithm for structure. These are two powerful computational tools that when combined, offer results closely mirroring those of already established methods, suggesting that the line of effort in computational studies offer useful results. The second insight offered is a basis for a computational model of the world. While only elevation was considered, the gradient approach was shown, regarding how to model the spread of people throughout the world.

Here will be the discussion of the results presented previously. Also included are implications from this research as well as limitations of what was able to be conducted. Further extensions are offered, some of which are underway now.

4.1 Insights and Implications

First, considering the phylogenetic aspects of the project, what was shown was a successful method for classifying languages into families based on their Swadesh lists. What can be learned from this is twofold: first, that the metric used, the Jaro similarity, is able to, in some capacity, capture language change. This implies that a model of language change that uses the Jaro similarity to define edit distance may be useful and accurate. The second implication from this line of effort is the hypotheses that may be conjectured from output. Particularly if more data is used, anthropologists, linguists and computer scientists may be able to begin to make conjecture of a

farther-reaching nature. The ideas of large language families, branching over multiple major classifications of Indo-European languages have swirled around the linguistic community for decades, but have failed to gain much traction. With this advancement in phylogenetic analysis, the greater pattern recognition of computers can be used to make conjectures of these macro-families.

Secondly, concerning the modeling of the Earth's surface, while a truly accurate model may be very elusive as there is a great abundance of variable to consider, the spread of language may indeed be able to be based on the spread of people still. This presents the possibility that geospatial data can yield important insights into the spread of language. Here, elevation was used, and was seen to have some insights into the way language travels. It is seen in the example that there are some similarities between real-world history and the computational line of effort shown here. Perhaps even further conjectures can be made based on what is computationally available.

The map of Britain containing the representation of the movements of people across the surface does offer some interesting possibilities itself. Consider the following figure of the dialectal map of the same region:



Figure 9. A dialectal map of British Isles (Jonathan 2015)

Seen here are the various regional dialects that are representative of the U.K. While this research does not argue that this image juxtaposed with the generated model suggest any conclusive connections, aspects such as the barriers of the Scottish Highlands and wester Welsh seem to be present in both. The research here is suggested to be a computational stepping stone for further dialectal and sociolinguistic intrigue.

Third, and what is the next major focus of this research is the combination of these two concepts. Considering a reliable model for language change, and computational understanding of the movement of language throughout the Earth's surface, it would be natural to combine the two in an effort to create a model of how language changes and spreads, all in one. This would be useful to many different historical, anthropological, and linguistic fields. Not only in the ability to

confirm theories through a new line of effort, diverse from the previous ones, but to offer new and further reaching explanations and hypotheses.

4.2 Limitations and Extensions

As with any modeling project, limitations, often in the form of assumptions, are required to have a functional output, but can result in lower fidelity results. The first limitation appears in the limitation of computational capabilities. As with any big computational undertaking, limitations will occur. For this project, in particular, the incorporation of elevation data presented a challenge. Covering the entirety of the over 8,000 km distance that the Indo-European Language Family has spread with fine grain elevation data requires a significant amount of time to retrieve the data from the online source.

Another important factor regarding the geospatial data is other factors, such as habitability. Consider for example things such as climate and agriculture potential. These things have such a large bearing on human migration that a model would much less useful without them. Consider the planes of Siberia. Even though the model here would say that there would be high rates of language spreading, history would disagree, as the region is difficult to inhabit due to a hostile climate.

Another real-world consideration that is left out of the model is the role of empires. Vast empires and kingdoms are often the reason that one language succeeds over another. This is a smaller subset of a larger considerations, that of competition. Competition modeling is a rich field, which is often applied to languages. Incorporating these into the model will produce higher fidelity results.

Concerning the phylogenetic clustering methods, departure from orthographic representation of words can be used to determine the way language changes over time. For this research, the Romanized versions of these words was used because of data availability and the fact that orthography can reveal relations. Work has already been conducted to use the International Phonetic Alphabet as a way to transcribe the Swadesh lists, so that differences in script and spelling will not hinder this method. While there is still validity in what was done here, as the results appear to match already established methods, one would want to use the purest transcription possible (IPA) to conjecture about specific sound changes.

Perhaps the most crucial extension for this project is the combination of modeling language change and language spreading. The two lines of the effort can be combined together to gain information about the way languages change. What is important about this is the possibilities of simulations. These simulations which can span centuries, can help determine the correct past, because a model which incorporates a lot of data, can simulate many possibilities, and the one that results in the most accuracy to real-world occurrences, may offer insight as to how languages have truly changed and evolved over time.

Appendix A Swadesh Lists (First 10 Entries of each Language)

English	Dutch	Luxembourgish	German	Danish	Swedish	Icelandic	Nynorsk	Latin	Portuguese
I	ik	ech	ich	jeg	jag	eg	eg	ego	eu
you	jij	du	du	du	du	thú	du	tu	tu
he	hij	hien	er	han	han	hann	han	is	ele
we	wij	mir	wir	vi	vi	vid	vi	nos	nos
you	jullie	dir	ihr	I	ni	thíð	de	vos	vos
they	zij	si	sie	de	de	their	dei	ii	eles
this	deze	desen	dieser	denne	denna	thessi	denne	is	este
that	die	deen	jener	den der	den	hinn	den	iste	esse
here	hier	hei	hier	her	har	her	her	hic	aquí

Spanish	French	Italian	Romanian	Sanskrit	Pali	Hindi	Urdu	Punjabi	Gujarati
yo	je	io	eu	aham	aham	mai	mai	me	hu
tu	tu	tu	tu	tvam	tvam	tum	tum	tu	tame
el	il	lui	el	sa	sa	vah	vah	uh	te
nosotros	nous	noi	noi	vayam	vayam	ham	ham	asi	ame
vosotros	vous	voi	voi	yuyam	tumhe	tum	tum	tusi	tame
ellos	ils	loro	ei	te	te	ve	ve	uh	teo
este	ce	questo	acest	idam	sa	yah	yah	ih	a
ese	ce	quello	acel	tat	tad	vah	vah	uh	pelu
aquí	ici	qui	aici	atra	idha	yaha	yaha	itthe	ahi

Lithuanian	Latvian	Czech	Polish	Slovak	Bulgarian	Macedonian	Croatian	Russian	Ukrainian	
as	es	ja	ja	ja	az	jas	ja	ja	ja	
tu	tu	ty	ty	ty	ti	ti	ti	ty	ty	
jis	vins	on	on	on	toj	toj	on	on	vin	
mes	mes	my	my	my	nie	nie	mi	my	my	
jus	jus	vy	wy	vy	vie	vie	vi	vy	vy	
jie	vini	oni	oni	oni	te	tie	oni	oni	vony	
sis	sis	tento	ten	tento	tozi	ova	ovaj	etot	cej	
tas	tas	tamten	tamten	ten	onzi	ona	taj	tot	toj	
cia	seit	zde	-	tu	tuk	ovde	ovdje	tut	tut	
Marathi	Assamese	Bengali	Kashmiri	Sinhalese	Romani	Farsi/Persian	Kurdish	Welsh	Irish	Gaelic
mi	moi	ami	bi	mam	me	man	min	mi	me	mi
tu	tumi	tumi	tsi	oba	tu	to	to	ti	tu	thu
to	i	se	suh	eya	voj	u	ew	ef	se	e
amhi	ami	amra	asi	api	ame	ma	eme	ni	muid	sinn
tumhi	tumi	tomra	tosi	oyala	tume	shoma	ewe	chi	sibh	sibh
he	xihot	tara	tim	ovuhu	von	ishan	ewan	hwy	siad	'ad
ha	ei as	e	yih	meya	kado	in	em	hwn	an	an
to	xei	o	tih	ovhu	kodo	an	ew	hwnnw	an	an
ithe	iat	ekhane	yor	mehi	kathe	inja	ere	yma	anseo	an-seo

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